5 Steps to Practically Implement AI Techniques



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Moving from "I want to use AI" to a tactical approach aimed at practically and sustainably solving business problems, while managing expectations, does not require superpowers. CIOs can follow these five steps to pursue an AI strategy in a pragmatic fashion.



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Key Challenges

- Many organizations spend a lot of time, money and political equity trying to define an artificial intelligence (AI) strategy instead of focusing on business problems.
- When it comes to AI, the first question many CIOs, and even line of business (LOB) leaders, ask is: "Which platform should I use?" But starting with the technology is like "putting the cart before the horse."
- When implementing AI techniques, AI skills and a proper set of data (linked to practical use cases) should be front and center, but many organizations only make these second-order considerations.
- Organizational issues are important for the sustainability of Al efforts, but they are often promoted at the expense of a rigorous business use case selection process.

Recommendations

CIOs looking to apply AI in the enterprise should:

- Invest only in the most impactful, measurable business use cases that are achievable in a limited time frame.
- Hire the right analytics, IT and business skills necessary for those business use cases.

- Assign data stewards to select, secure and prepare the appropriate data linked to the selected use cases.
- Choose the most suitable AI techniques for the problem to be solved, along with the right tools aligned with the selected skills.
- Build an AI expertise organizational structure designed for knowledge transfer and problem solving.

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Strategic Planning Assumptions

By 2020, 50% of organizations will lack sufficient artificial intelligence (Al) and data literacy skills to achieve business value.

By 2023, 80% of all digital business industry visions will be powered by Al selected from Al industry use cases.

Introduction

Establishing an artificial intelligence (AI) strategy before first testing the organization's readiness to adopt AI techniques is like establishing a battle strategy without knowing if troops have been trained and prepared (unknown skills), without any intelligence regarding the enemy movements and capabilities (unknown data), zero knowledge about the weapon systems at your disposal (unknown technology), and no understanding of the objectives (unknown goals).

The practical introduction of AI techniques within an organization of any size can be achieved through five steps:

- 1. Use cases Build a portfolio of impactful, measurable and quickly solvable use cases.
- 2. **Skills** Assemble a set of talents pertinent to the use cases to be solved.
- 3. **Data** Gather the appropriate data relevant to the selected use cases.
- 4. **Technology** Select the AI techniques linked to the use cases, the skills and the data.
- 5. **Organization** Structure the expertise and accumulated Al know-how.

This five-step formula is a tactical approach to the introduction of AI techniques, favoring a quick time-to-value perspective. It is not a strategic, longer-term outlook, which can be developed once the organization has established its current strengths and weaknesses, culturally and technologically, in terms of leveraging those techniques.

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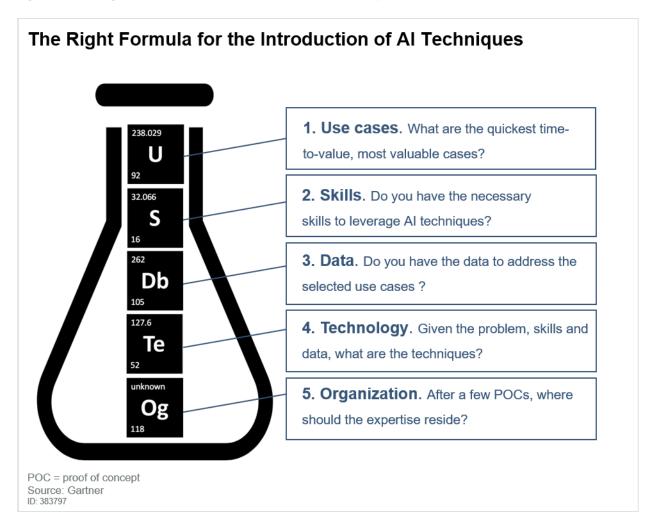


Figure 1. The Right Formula for the Introduction of Al Techniques

Analysis

Step 1. Build a Portfolio of Impactful, Measurable and Quickly Solvable Use Cases

Measurable outcomes should be the foremost goal of this first step. As with most successful Al and machine learning (ML) initiatives, the idea is to start with the answer, and an answer that is as complete as possible. A clear understanding of its final business impact should be the start of every project leveraging Al techniques. Line-of-business (LOB) stakeholders, for example, should be able to clearly articulate the tangible business benefits they expect to see from Al. Those expectations may change or evolve as the project progresses, but firmly establishing them at the outset is important.

In a recent survey conducted by Gartner, respondents stated that they are planning a sharp increase in deployed Al projects — from five new projects on average in the next year, to nine the

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year after, and 13 the year after that. Moreover, according to Gartner's most recent CIO survey, about 14% of CIOs report that they have already deployed AI solutions, and 23% report that they will be doing so in the next 12 months.

Three principles are important for this foundational first step:

- Select the right (i.e., measurable, impactful, feasible) use cases.
- Describe their value propositions as clearly as possible.
- Do not compromise on metrics expectations and watch their evolution closely.

Selecting Use Cases

Many techniques are possible to establish a small portfolio of use cases. Gartner provides guiding principles and practical examples for organizations to select and prioritize the most promising areas for AI techniques to be leveraged with sample domains and industry use cases (see "Toolkit: How to Select and Prioritize AI Use Cases Using Real Domain and Industry Examples"). Other use cases can be found in "AI Use Cases, Tales From the Trenches: A Gartner Trend Insight Report."

Simple instruments such as the impact versus feasibility matrix (Figure 2) can help in quickly and clearly prioritizing use cases.

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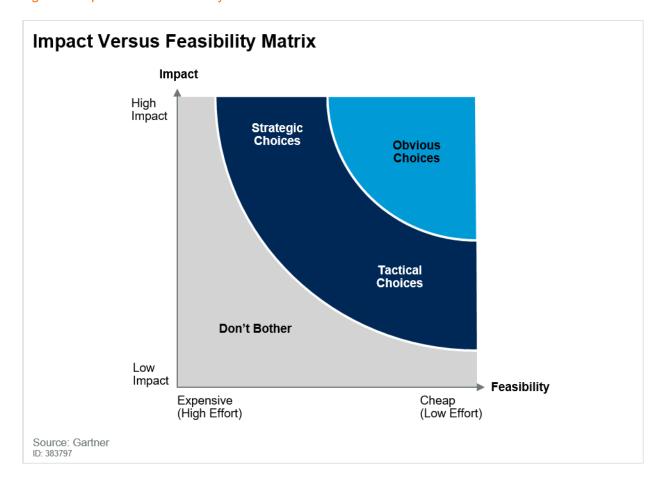


Figure 2. Impact Versus Feasibility Matrix

Think big, start small, act fast ... and deliver results in 9 weeks!

In selecting use cases, another important criterion should be time. Despite the very large number of combinatory factors, a simple rule-of-thumb, nine-week sequence has shown merit in a large number of POCs: Think big, start small, act fast. The point is to pick a critical problem for the organization, one that other techniques have not been able to tackle (think big). But scope the problem to fit it into the nine weeks mandate (start small). Finally, start iterating around its execution as quickly as possible to rapidly uncover any issues and rescope as necessary (act fast).

Describe Use Cases as Clearly as Possible

Even for small and rapid POCs, and especially when it comes to AI techniques, value propositions need to be articulated as clearly as possible. A value proposition canvas such as that shown in Figure 3 can be a powerful tool for CIOs to transparently assess business outcomes and potential barriers.

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Figure 3. Value Proposition Canvas

Problem	Key Activities	Value Proposition		Differentiated Advantages	Customer Segments/ User Types
What user problem are we focusing on solving?	What key activities does our value proposition require?	 What value do we deliver to the user/customer? What value do we bring to the organization? 		What unique value can be derived from solving the problem?	What type of users should the solution be focused on?
	Key Resources	What does the minimal viable product look like?		Channels	
	What key resources does our value proposition require?			How is the solution best integrated into existing processes?	
	Key Metric	s (Which metrics	are indicat	ors of success?)	
Cost Structure			Revenue Streams		
		Estimated Retur	n on Inves	tment	

Do Not Compromise on Established Metrics

The Gartner Business Value Model can help you to establish an appropriate set of metrics (see "The Gartner Business Value Model: A Framework for Measuring Business Performance"). This model is a structured framework and definition of nonaccounting metrics that can be applied generically to help organizations identify how their business activities will impact financial performance.

Creating concrete, measurable metrics can also help organizations apply three types of value to the AI techniques they wish to implement:

- Information value (improving the information management process itself).
- Business value (improving business processes).

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 Stakeholder value (what the data and analytics mean for stakeholders such as customers, partners, shareholders and society at large).

See "Data and Analytics Strategies Need More-Concrete Metrics of Success."

However, as mentioned earlier, given the unconventional approach that AI techniques represent, early adopters should keep an open mind as metrics may change or evolve as their exploration advances.

See also:

- "Build the Al Business Case" e-Book
- "CIOs Can Manage the Risks of Al Investments"

Step 2. Assemble a Set of Talents Pertinent to the Use Cases to Be Solved

Three personas provide an ideal balance to initiate AI efforts, depending on the use cases that have been prioritized:

- An Al specialist who, for example, could specialize in ML, rule-based systems or natural language processing (NLP) systems.
- An IT professional who understands the current state of IT capabilities, potential integration points and source systems, and their potential limitations.
- A subject matter expert (SME) who understands the business requirements and metrics.

These personas will form a complementary triumvirate of AI, IT and domain expertise. But in each area of expertise, a host of skilled personas will be central to solving the proposed use cases (see Figure 4).

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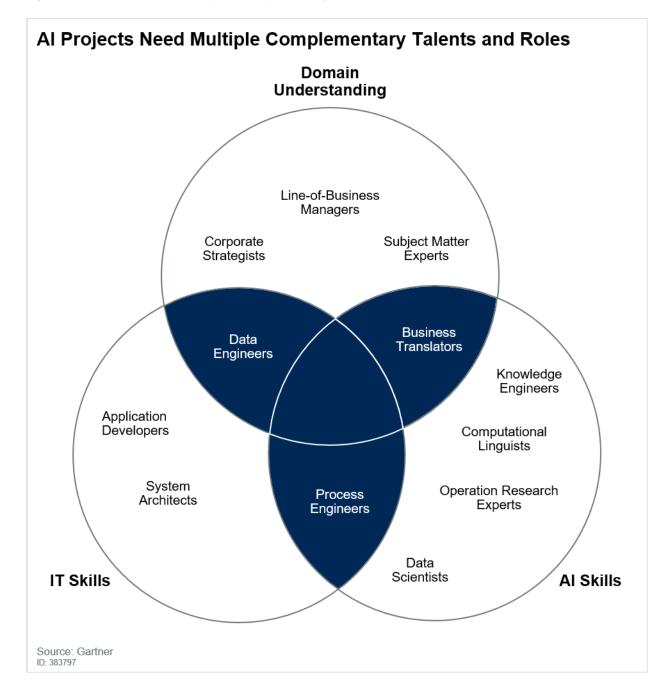


Figure 4. Al Projects Need Multiple Complementary Talents and Roles

Despite the hype, it turns out that AI skills are not necessarily extremely scarce, expensive or mysterious. Curious database administrators or mathematically inclined data engineers can become great data scientists; they do not need a Ph.D., or even Python skills. The latter might sound iconoclastic in today's fashionable ML world, but the fact of the matter is that it is possible to build valuable predictive analytics models without writing one line of code — even if SQL knowledge remains central to ML. What is required, however, is a combination of sound ML knowledge, a

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strong understanding of statistics principles, and a passionate curiosity for data exploration and manipulation.

Of equal importance are collaboration skills. From the three areas of expertise mentioned above, people working in tight collaboration mode is a surer path to success than a single person's deep knowledge in one of those areas mired with unrealistic expectations. Motivated, open-minded, competent and focused champions, often coming from the organization's ranks rather than from outside, is a better recipe for successful POCs.

Al Thrives Through Data Literacy

In addition to business benefits, early POCs will deliver important lessons on the organization's readiness to adopt AI techniques. Original baseline skills might need to be enhanced through upskilling programs using local academic programs (in the form of certificates), or through online courses (for example, Coursera, Udemy, DataCamp). However, from that baseline, to stay competitive and ensure the scalability of their progress, enterprises will eventually have to move toward a deeper educational program.

Gartner research such as "Artificial Intelligence Demands That CIOs Foster a Data-Literate Society" points to the fact that, while conversant in the "people, process and technology" capabilities of business change, most executives and professionals do not "speak data" fluently as the new critical capability of digital society (see Figure 5).

Data Is the New Core Capability of Digital Business

People
Process
Technology

Source: Gartner

Figure 5. Data Is the New Core Capability of Digital Business

See also:

"Information as a Second Language: Enabling Data Literacy for Digital Society"

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- "Toolkit: Enabling Data Literacy and Information as a Second Language"
- "Staffing Data Science Teams: Map Capabilities to Key Roles"
- "Organizational Principles for Placing Data Science and Machine Learning Teams"

Step 3. Gather the Appropriate Data Relevant to the Selected Use Cases

The quality and relevance of your data should preside over volume.

A myth plaguing early AI exploration is that you need massive amounts of data to build successful AI models. In fact, many successful use cases can be achieved using a reasonable amount of data, as long as that dataset is of quality (i.e., normalized, complete, diversified). The lack of volume can always be compensated for through a reduction in project scope, but a lack of data quality invariably leads to POC failure. Probabilistic reasoning techniques such as ML rely heavily on data to deliver insights; therefore, this is where data quality problems are most acute — throughout the ML life cycle.

In addition to the data quality challenges outlined in Figure 6, it is important to remember that the processes in place — that is, to ensure the quality of the data — will be iterative.

However, a "reasonable amount of data" could mean different things depending on the AI techniques that end up being selected. ML techniques will require significantly more data than logic-based or optimization techniques. The same is true for NLP systems, whether they leverage subsymbolic (ML techniques) or traditional symbolic (linguistics) techniques. The skills identified in Step 2 will be critical in making that determination.

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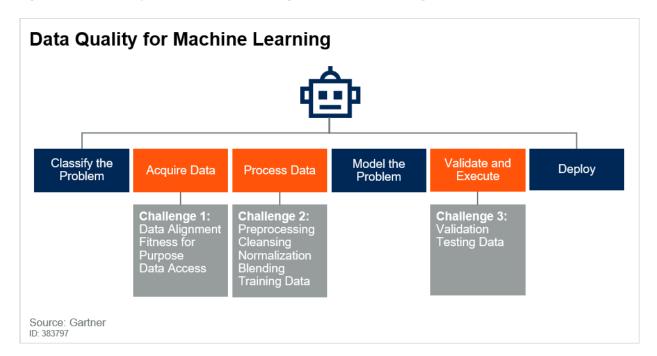


Figure 6. Data Quality in the Machine Learning Process and Challenges

Data Pipelines

While gathering the data relevant to the business problems selected in Step 1, beyond its quality and completeness, it is also important for CIOs to understand the sustainability of that data, i.e., are the sources of that data anecdotal or systematic? Are they partial, complete, discrete or continuous? Can the data be obtained on a subsecond basis, daily, weekly, etc.? This consideration will be crucial for the potential scalability of the POC, and it could be instrumented through the implementation of data pipelines. This practice encompasses initiatives that are described in detail in "Enabling IoT Data Pipelines for Machine Learning Inference."

See also:

- "Making Machine Learning a Scalable Enterprise Reality From Development to Production"
- "Data Engineering Is Critical to Driving Data and Analytics Success"

Step 4. Select the Al Techniques Linked to the Use Cases, the Skills and the Data

The majority of AI techniques are mature and have been around for decades. Many are suited for specific problems, data and talents. For example, probabilistic reasoning techniques (like ML) are particularly apt to uncover hidden patterns in a large amount of data, like fraud patterns, churn issues, or risk variables. But ML techniques require a sufficient amount of very high quality data, along with analysts who are conversant in analytical mechanisms and algorithms.

At the other end, finding a perfect balance in inventories, perfecting routes within a supply chain problem, urgently generating a workable plan under multiple hard constraints in a limited amount of

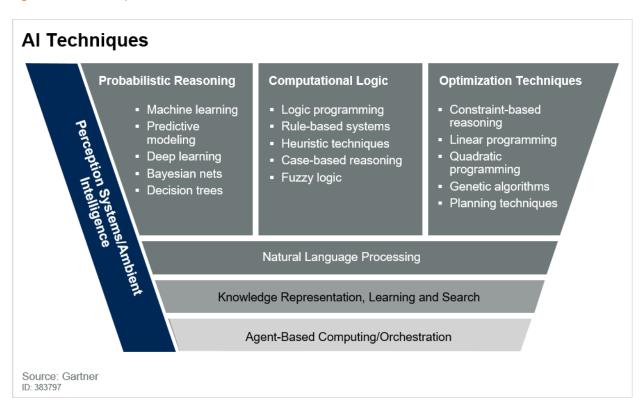
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time — such as managing landing, gate and crew assignments at an international airport during a snow storm — will most certainly require the use of optimization techniques. These techniques require talents in operations research and the ability to appropriately gather data, especially while considering the operationalization of those models in production.

Again, there are multiple AI techniques (see Figure 7) that might already be integrated within enterprise solutions (e.g., SalesForce, SAP, Oracle), decision-modeling solutions (e.g., FICO, Enova Decisions, ACTICO), or pure-play techniques (e.g., RapidMiner, KNIME, FlexRule, Decisions, Gurobi, Frontline Systems, Attivio, Narrative Science, Maana, Grakn, Swarm Technology, Matroid, Deepomatic, PROPHESEE).

It is also possible to leverage these techniques via many open-source libraries and platforms.

Figure 7. Al Techniques



However, when it comes to the "technology step," a successful POC does not exclusively focus on AI techniques. The surrounding technology fabric into which the techniques will be woven is equally important. The IT infrastructure (for example, resources available to train algorithms and integrate with target systems), existing process automation software (where AI models will be integrated) and adequate user interfaces (to interact with those models) are among the other technology considerations that should be discussed at this stage.

See:

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"Artificial Intelligence Hype: Managing Business Leadership Expectations"

"Combine Al Techniques to Solve Business Problems"

"2018 Strategic Roadmap for Compute Infrastructure"

"How to Operationalize Machine Learning and Data Science Projects"

Step 5. Structure the Expertise and the Accumulated Al Know-How

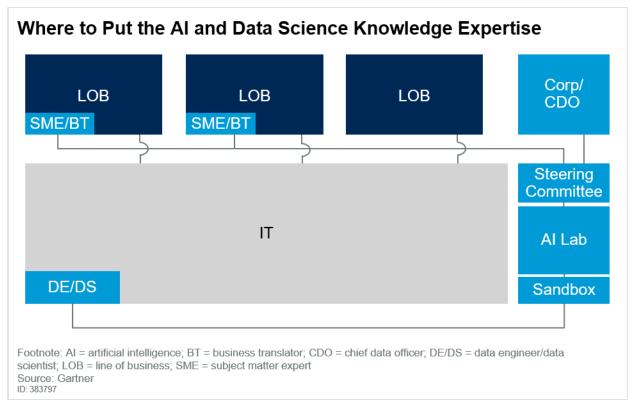
Al techniques are still "shiny objects" and CEOs are growing wary of the money invested and the lack of ROI that too often follows, even when POCs are successful. Executing a few POCs on various business problems enterprisewide should allow organizations to identify gaps in skills, data and technology, but also gaps in culture, readiness and general education about the Al discipline. The various levels at which Al techniques can be leveraged and complement human tasks should also be taken into consideration, as the appetite can vary widely from one department to another.

Al competence can reside in many areas of the business. From LOBs to the IT department, or other specific functional areas, enterprises tend to have pockets of skills that they tend to consolidate into competency centers.

Nonetheless, organizations tend to evolve toward a certain model (with a few variations) once they have gone through a number of experiments leveraging AI techniques. That organizational model is based on a separate "AI lab." The lab is independent of both the LOBs and the IT department, usually reporting to a neutral corporate function. The idea is to nurture intimate ties to the business while staying abreast of the organization's technical capabilities and investments, while at the same time staying in sync with the overall strategy. While still reporting to the lab, AI experts can perform "tours" within LOBs, working closely with subject matter experts (SMEs) and with IT professionals on the various ongoing projects, favoring a technical cross-pollination of the AI capabilities. That proximity also allows them to entertain serendipitous ideas from technical and business stakeholders (see Figure 8).

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Figure 8. Best Practices for the Organization of Al and Data Science Skills



Once the five steps above have been worked through a few iterations, the organization should consider a larger and more ambitious vision revolving around an AI strategy.

See:

"How Data Science Teams Leverage Machine Learning and Other Advanced Analytics"

"Organizational Principles for Placing Data Science and Machine Learning Teams"

Acronym Key and Glossary Terms

AI	artificial intelligence
ML	machine learning
LOB	line of business
POC	proof of concept
SME	subject matter expert

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Gartner Recommended Reading

Some documents may not be available as part of your current Gartner subscription.

"Survey Analysis: Moving Al Projects From Prototype to Production"

"What Is Artificial Intelligence? Seeing Through the Hype and Focusing on Business Value"

"Five Ways Artificial Intelligence and Machine Learning Deliver Business Impacts"

"Use 3 MLOps Organizational Practices to Successfully Deliver Machine Learning Results"

"Al Governance Spotlight: Early Lessons and Next Practices"

"How to Manage the Risks of Decision Automation"

Evidence

¹ **Gartner's AI and Machine Learning Development Strategies Study** was conducted via an online survey from 13 December through 30 December 2018 with 106 Gartner Research Circle Members — a Gartner-managed panel composed of IT and IT-business professionals.

To participate, respondents had to have AI or ML currently deployed or in planning at their organizations. Over half of qualifying respondents had an AI or ML project deployed, with most of the remainder expecting to deploy within the next year.

The survey was developed collaboratively by a team of Gartner analysts and was reviewed, tested and administered by Gartner's Research Data and Analytics team.

² The **2019 Gartner CIO Survey** was conducted online from 17 April through 22 June 2018 among members of Gartner Executive Programs, along with other CIOs. Qualified respondents were the most senior IT leader (CIO) for their overall organization or a part of their organization (for example, a business unit or region). The total sample was 3,102, with representation from all geographies and industry sectors (public and private). The survey was developed collaboratively by a team of Gartner analysts, and was reviewed, tested and administered by Gartner's Research Data and Analytics team.

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